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State of air pollutants and related health risk over Haryana India as viewed from satellite platform in COVID-19 lockdown scenario

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Abstract COVID-19 driven lockdown has affected air quality worldwide. Changes in air pollutants concentration, Air Quality Index (AQI), and associated Excess Health Risk (ER%) were assessed using satellite data of before (2019), and during (2020) COVID-19 periods in the industrially, agriculturally developed and highly populated area of Haryana in the northern region of Indo-Gangetic Plains. Parameters such as Aerosol Optical Depth (AOD), Particulate matters (PM), Sulphur Di-Oxide (SO_2), Nitrogen Di-Oxide (NO_2), Carbon Mono-oxide (CO), and Methane (CH_4) were derived using satellite data and validated using ground-based observations (n = 23). The coefficient of correlation (r) 0.91, 0.90, 0.95, 0.73, 0.81 and 0.80 were established with AOD, $PM_{2.5}$, PM_{10}, SO_2, NO_2 and CO, respectively. Significant reduction ($p < 0.005$) in the concentration of air pollutants, viz. 38% in AOD, 55% in $PM_{2.5}$, 61% in PM_{10}, 31% in SO_2, 10% in NO_2, 5% in CO and 1% in CH_4 were observed during lockdown. Significant ($p < 0.00$) improvement in air quality was observed due to a 44% reduction in pollution level, which led to the reduction in ER% by 71%, which is quite significant. AQI and ER% from satellite and ground showed a high r^2 i.e. 0.88 and 0.99 respectively, suggesting the potential application of satellite data for periodic AQI and ER% assessment.

Keywords Sentinel-5P · MODIS · AOD · AQI · Health risk

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1 Introduction

Air pollution is a result of intense anthropogenic activities on earth such as transport, industrialization, biomass burning, along with natural causes such as volcanoes and forest fire [1]. It is reported that the anthropogenic activities contributes approximately 80% increase in the pollution [2]. Thus reduced human activities would have resulted in a reduced level of air pollutants as observed at the global and regional level during the COVID-19 driven lockdown in 2020 [3–10]. COVID-19 has significantly impacted the socio-economic and environmental conditions of planet earth [3–23]. COVID-19 is a respiratory disorder of viral origin caused by novel coronavirus or SARS CoV-2 with symptoms of fever, dry cough, and breathing difficulty. The first case of COVID-19 was reported from Wuhan city, China in December 2019 and rapidly spread all across the globe. It has been declared as a global pandemic by the World Health Organisation (WHO) [24] on 11 March 2020, looking at its contagious nature and death severity (> 3,037,398 deaths worldwide till 22 April 2021). This was further taken as a serious note by the Government of India after the detection of the first case on 30 January 2020 from Kerala, India, which resulted in the three-phase lockdown viz. (1) March 24 to April 14, 2020, (2) April 15 to May 3, 2020, and (3) May 4 to May 17, 2020, over the whole country. The first two phases were strict, while the last one was a relaxed lockdown.

The lockdown has significantly reduces the pollutants concentrations and improved Air Quality by reducing the transport, industrial activities, and other anthropogenic activities all across the globe [4, 6, 11–15, 25, 26]. Wang et al. [15] observed a reduction of 36–53% in the concentration of Nitrogen Dioxide (NO_2) over six megacities of China. Fang et al. [16] observed a reduction of 18–45%, 17–53%, 47–64%, 9–34%, and 16–52%, respectively for particulate matters 2.5 ($PM_{2.5}$), particulate matters 10 (PM_{10}), NO_2, Sulfur Dioxide (SO_2) and Carbon Monoxide (CO), over urban agglomerations in China, during lockdown period relative to pre-lockdown period. Mendez-Espinosa et al. [17] reported a reduction of 60%, 44%, and 40% respectively in the concentration of NO_2, PM_{10}, and $PM_{2.5}$ over South America during the strict lockdown amid COVID-19. Siddiqui et al. [6] reported a total of 46% reduction in average NO_2 values and 27% improvement in (Air Quality Index) AQI values over the eight cities of India due to COVID-19 driven lockdown. However, a complete study on the effect of COVID-19 driven lockdown on air pollutants, AQI, and ER% is lacking particularly for Haryana, India, though required on an urgent basis looking at the lethality of disease (a total of 6% of global deaths in India till 22 April 2021, and Haryana is among the most affected states) possibly due to the consistent high pollution level [1, 6, 27–29]. Aerosol Optical Depth (AOD) which is a key parameter of air quality (which indicates column integrated particulate matters) gets reduced in response to COVID-driven lockdown [26]. Similarly AQI is a range of index values that indicates the air quality (Good = 0–50, Satisfactory = 51–100, Moderate = 101–200, Poor = 201–300, Very Poor = 301–400, and Severe = 401–500) of a location or region significantly get reduces during lockdown [30]. ER% which is the excess health risk associated with the pollutants level excess than the standard concentration [5, 28] also gets reduces in response to lockdown. Since the values of air pollutants, AQI, and ER% have been identified as one of the serious threat to human health (9 out of 10 people breathe air containing high levels of pollutants, 7 million deaths annually, and 12.5% of the total deaths worldwide), and environment at global and local scale [24, 31–35] their reduction may reduce the health risk and improve the environmental quality. It is also reported that the areas with high air pollution levels were found to be affected more with COVID-19 and its severity [6, 29]. Thus, it is the need to identify the hotspot of air pollution and take necessary actions to combat it on an urgent basis, so that the risk of COVID-19 like diseases may be reduced in the future [17–19, 36].

Ground-based monitoring stations provide data for the assessment of pollution level and its hotspot. Setting up ground-based stations with the capability to measure these criteria pollutants require huge maintenance, operating manpower, and a huge amount of money which is not realistic at least in Indian conditions [1]. Thus, it is required to use low-cost technologies and surrogate variables like AOD from satellite that can provide relevant information about air pollution and pollutant level for further AQI and ER% assessment. Satellite-based assessment of air quality parameters (such as AOD, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and CH_4) is found to be a potential way of regular and cost-effective monitoring of these pollutants at a spatial scale [1, 4, 6, 37–39].

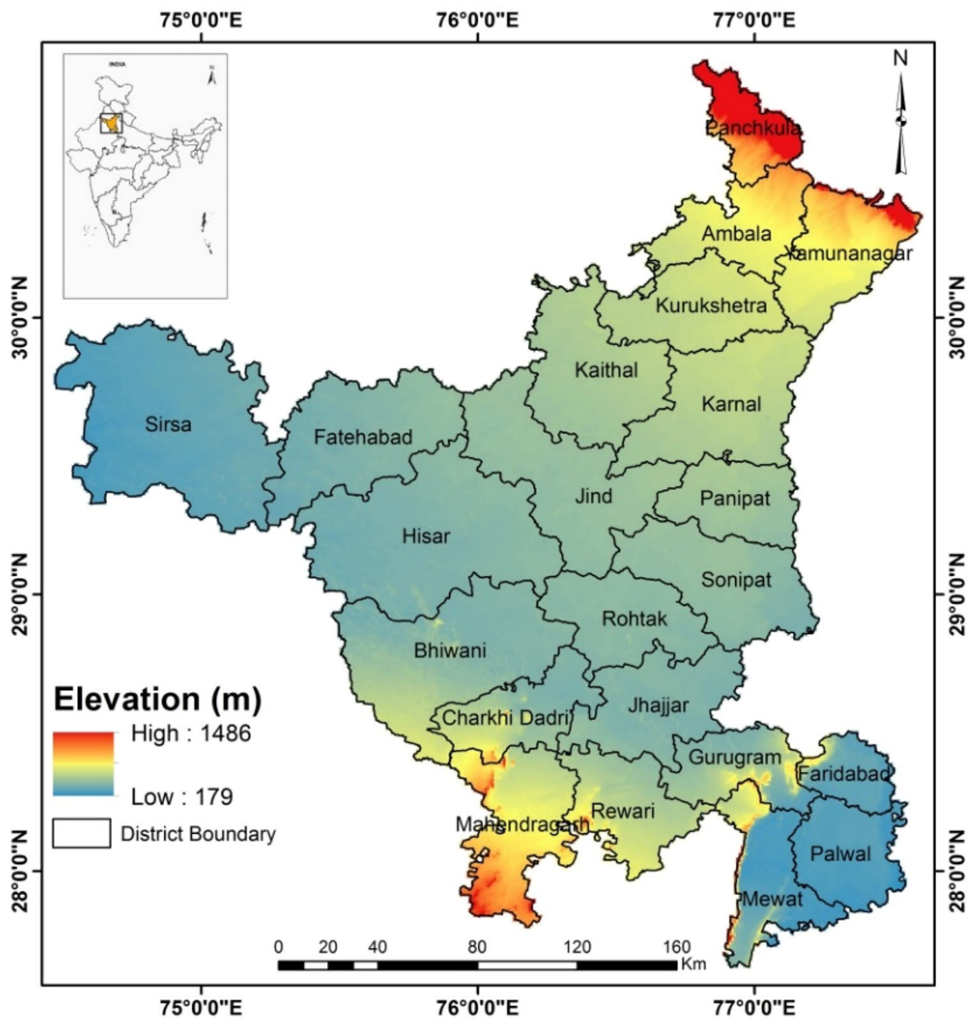
The goal of reducing pollutant levels by 20 to 30% till 2024 (as decided in National Clean Air Programme, NCAP) from its base year 2017 was observed to be a tough task, looking into the requirement of economic growth and industrialization. However, COVID-19 driven lockdown has shown glimpses of reduced air pollution in 2020 worldwide, including India [4, 6, 11–15, 25, 26]. Though, the assessment of effect of COVID-19 driven lockdown on air quality both at global [11] and regional [4, 6, 11–15, 25, 26] scale taking ground [5, 15] and satellite-based [4, 6, 12] observations are available, no study reported the satellite-based AQI and ER% assessment over any region of the globe and over the Indian region (Haryana) in particular. Furthermore, there is no reported study for the validations of Sentinel-5P satellite-based pollutant products concerning ground observations which gives novelty to the current work. We compared the satellite-based concentrations of various air pollutants/indicators including AOD, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and CH_4 in the month of April 2019 (no lockdown) and 2020 (completely falling within the strict lockdown period in India) to understand the effect of lockdown on the concentrations of these pollutants/indicators. The study is taken up with the following key objects: (1) Validation of satellite-derived air pollutants using ground-based observations, (2) Assessment of the state of air pollutants using these validated satellite-based measurements, (3) Utilisation of these measurements for the assessment of AQI and ER%.

2 Method

2.1 Study area

The study area (Haryana state) is situated in the northern part of India and bounded within the latitude of 27.64258158 to 30.90568992 and longitude of 74.46724953 to 77.53797611 (Fig. 1). The geographical area of the state is 44,212 km^2 with a total population of 25,350,000. Haryana has two major physiographic regions: (a) the flat alluvial plain covering most of the state and (b) a strip of the highly dissected Shiwalik range in the North-East (including the narrow foothill zone). The Haryana state falls in the Indo-Gangetic region which is always high in air pollutant concentration level [6, 31, 40–43].

Fig. 1 Study Area representing the state of Haryana



2.2 Method in brief

For this study, the two phase methodology was adopted. PM estimation is being done (through a regression analysis using Ground-based PM and Satellite-based AOD) in the first phase, and AQI and ER% were generated (over Haryana through the validated Sentinel-5P pollution products including NO_2, SO_2, CO, and CH_4 and estimated PM) in the second phase. Two times data (Table 1) were selected based on COVID-19 driven strict lockdown i.e. during (April 2020) and prior to this (April 2019).

The satellite-based pollutant concentrations were validated with respect to ground-based pollutant concentrations at 23 stations. After confirmation of the accuracy of satellite-derived pollutant parameters, the impact of COVID-19 driven lockdown were assessed taking the % difference into the consideration. Further, AQI were estimated, using these pollutants parameters ($PM_{2.5}$, PM_{10}, SO_2, NO_2 and CO) and a model suggested by CPCB for each cell of 3 × 3 km spatial resolution in ArcGIS 10.6 desktop software. The ER% was also estimated in the same fashion by using existing models [5]. The impacts of COVID-19 driven lockdown were assessed both for AQI and ER% at the final stage taking % difference into the consideration. Final maps were prepared in ArcGIS 10.6 desktop software. The step-wise method is summarised in Fig. 2.

2.2.1 *Satellite data processing and validation*

2.2.1.1 Processing MODIS AOD product was downloaded from National Aeronautic Space Administration (NASA) Earth explorer web site and pre-processed using MODIS MT tool kit. The pre-processed data were used for statistical analysis and comparison before (April, 2019) and during (April, 2020) lockdown period. Differences obtained in AOD due to COVID-19 driven lockdown was tested with t-test (both one and two tailed at $p = 0.05$). The validated products of MODIS were used for the prediction of Particulate Matter (PM) concentration.

Table 1 Characteristics of datasets used in the current study

Data used	Sensors/medium	Algorithm	Spatial resolution	Spectral regions	Swath	References
AOD-Level-2 MODIS/Terra (MYD04)	Moderate Resolution Imaging Spectroradiometer (MODIS)	dark target retrieval algorithm Collection-6	3 × 3 km	36 spectral bands between 0.405 μm to 14.385 μm	2330 km	[49–52]
Sentinel-5 Precursor (S-5P)	TROPOspheric Monitoring Instrument (TROPOMI)	Differential Optical Absorption Spectroscopy (DOAS) algorithm, and slant column density (SCD) using log-ratio of the observed UV–visible spectrum	7 × 7 km at nadir	Ultraviolet (270–320 nm), the visible (320–490 nm), the near-infrared (710–775 nm) and the shortwave infrared (2305–2385 nm) (2 spectral bands in each spectral range)	–	[12, 52–55]
Ground-based air pollutants such as PM2.5, PM10, SO2, NO2 and CO, and AOD	Ground station of Central Pollution Control Board (CPCB), and Aerosol Robotic Network (AERONET)	–	23 ground stations (Table 3)	Capable in measuring PM2.5, PM10, SO2, NO2, CO, and AOD	–	[27, 56, 57]

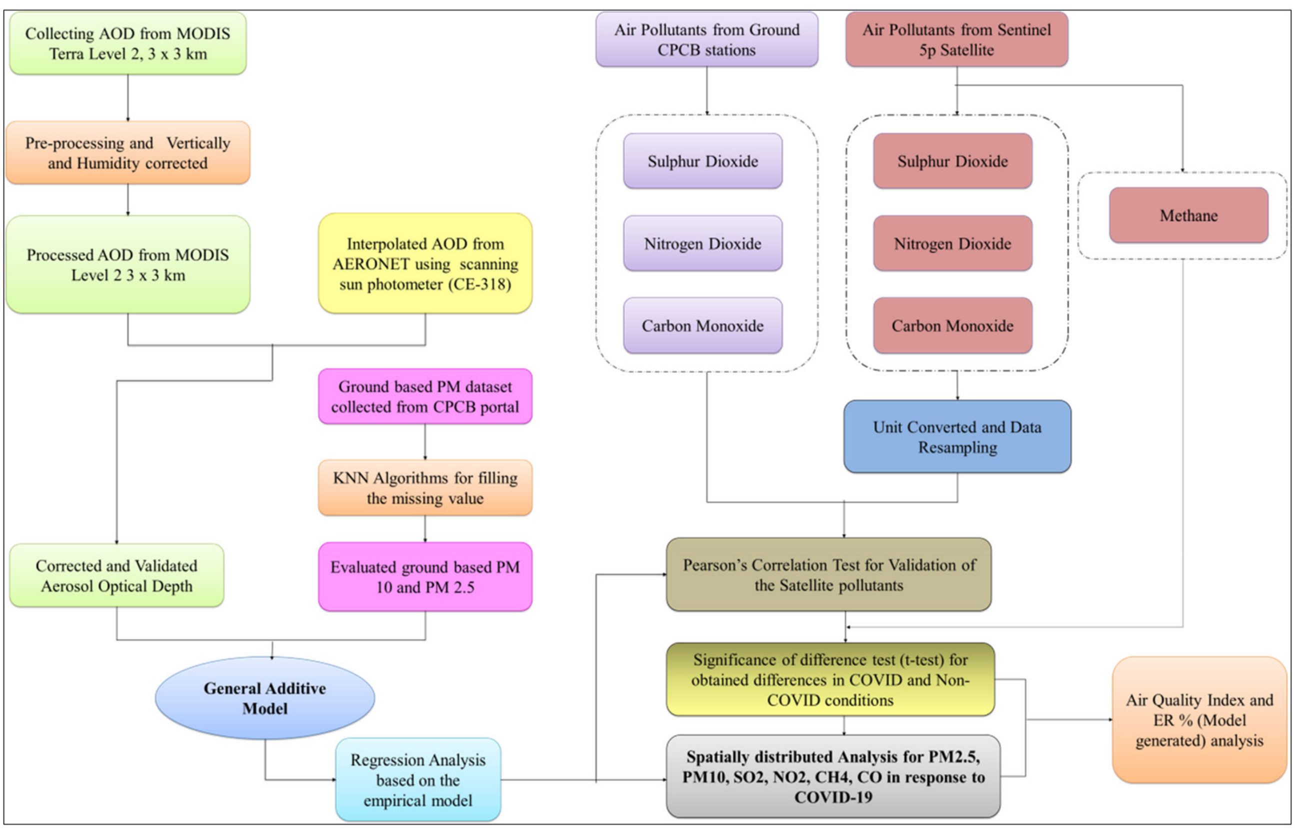


Fig. 2 Flowchart of the methodology adopted in this study

Sentinel 5P data from TROPOMI were processed using SNAP tool. Data spanning from 1 to 30 April were downloaded for two years i.e. 2019 and 2020 on a daily basis. An average were then made for whole month and compared. Values of satellite-based pollutants (SO_2, NO_2 and CO) were extracted for each of the ground stations and compared with average values of the ground-based pollutants. Ground data for CH_4 was missing and thus no validation was done for CH_4.

2.2.1.2 Satellite data validation Satellite observations from Sentinel-5P represent an aggregated concentration of pollutants in the tropospheric column [44]. The major problem in the validation of these pollution parameters is their measurement unit which is in mol/m^2, whereas ground-based observations are provided in μg/m^3. Similar units are essentially required for the validation of the satellite-based products from ground-based observations. So unit conversion of the satellite data from mol/m^2 to μg/m^3 is done initially. Firstly, we converted mol/m^2 into the part per billion (ppb), so to get an order of magnitude estimate for the ppb value and further divided the values by the height of the troposphere i.e. 10 km (0.1 mol/m^2/10 km = > 0.00001 mol/m^3). Then we use a gas concentration converter to convert the unit from mol/m^2 to mol/m^3. The whole concept may be summarised following the arithmetic expressions (Eqs. 1–4) as suggested by [45, 46]:

$$0.1\,\mathrm{mol/m^2} = 224\,\mathrm{ppb} \tag{1}$$

For tropospheric column we have

$$\frac{0.1\,\mathrm{mol/m^2}}{1\,\mathrm{km}} = 0.00001\,\mathrm{mol/m^3} \tag{2}$$

From Eqs. (1) and (2), we have

$$0.00001\,\mathrm{mol/m^3} = 224\,\mathrm{ppb} \tag{3}$$

Now, further the methods for converting ppb into μg/m^3 [45]:

$$\mathrm{\mu g/m^3} = \frac{\mathrm{ppb} \times 12.187 \times (\mathrm{M})}{(27.15 + \mathrm{T\,^\circ C})} \tag{4}$$

where M = molecular mass (SO_2 = 64, NO_2 = 46, CO = 28 and CH_4 = 16), T = Surface Temperature (which is taken on average of April month as 32 °C), So putting above value in Eq. 4, we have,

$$\begin{aligned}
&\text{For } SO_2 \quad 1\,\mathrm{ppb} = 2.556\,\mathrm{\mu g/m^3}\\
&\text{For } NO_2 \quad 1\,\mathrm{ppb} = 1.837\,\mathrm{\mu g/m^3}\\
&\text{For CO} \quad 1\,\mathrm{ppb} = 1.118\,\mathrm{\mu g/m^3}\\
&\text{For } CH_4 \quad 1\,\mathrm{ppb} = 0.639\,\mathrm{\mu g/m^3}
\end{aligned}$$

The data was further normalised using KNN method as suggested by [47].

For the ground data, the heterogeneity is quite high for validation purposes. So to regularize the data, first, we have to fill in the missing values, so as to have continuous data. For that KNN method was used with a weighted average of the nearest neighbour values. The Eq. (5) used for that is mentioned below [47]:

$$\hat{y} = f(x) = \frac{1}{k}\sum_{j=1}^{k} y_{i_j} \tag{5}$$

where $\hat{y}$ = predicted value for the missing values, y_i = real valued target as training data for ith observation, k = KNN scale factor.

After the filling of the missing value, the data was ready for validation. This has also been suggested that a process called scaling may provide more reliable results for validation. Thus, the Scaling was performed using the method suggested by Patro and Sahu [48] however, the final results were presented with normalized data only to maintain the consistency of the units of the pollution parameters. For the validation we have used correlation method in R software (R 4.0.5 for Windows). Correlation is a bivariate analysis that measures the strength of association between two variables and the direction of the relationship. Ground data from 23 ground stations and relative point value depicted from satellites are taken as input data.

2.2.2 Assessment of impact of COVID-19 on air pollutants

Satellite-based pollutant concentration for $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO and CH_4 were obtained for the April month for the year 2019 and 2020 at each ground station. Further, the significance of differences obtained in the pollutant concentration at each station were tested using t-significance test in microsoft excel for conforming our null hypothesis. Average of all the locations were then estimated for concluding the over all reduction in the pollutant concentration over the study area due to COVID-19 driven lockdown. District-wise statistics was also estimated for the assessment of impact of COVID-19 driven lockdown on average concentration of pollutants at district-level.

2.2.3 Calculation of air quality index (AQI)

Standard model suggested by CPCB [30] has been used for the calculation of AQI. The criteria pollutants from satellite based measurements including $PM_{2.5}$, PM_{10}, SO_2, NO_2 and CO were used for AQI estimation. The average pollutant concentration at each location (23 representing districts of the Haryana) were collected from satellite data only and subjected to the criteria set by CPCB for Indian conditions. The AQI of the year 2019 for each station were then compared with the respective AQI of the year 2020 and differences were tested using t-test of significance. The formula used for AQI is presented as Eq. 7 [30]:

$$AQI = \sum_{1}^{n} max\left(\frac{I_{HI-I_{LO}}}{B_{HI-B_{LO}}} \times (C_P - B_{LO}) + I_{LO}\right)_{1\ldots n} \quad (6)$$

where I_{HI} = AQI Value Corresponding of the B_{HI}, B_{HI} = Greater Breakdown Concentration, I_{LO} = AQI Value Corresponding of the B_{LO}, B_{LO} = Smaller Breakdown Concentration, C_p = Concentration of Pollutant, 1…n = Pollutants taken.

Similar criteria [i.e. 30] were used for the spatial mapping of AQI. The sentinel-5P data were resampled to a grid of 3 × 3 km spatial resolution from its original 7 × 7 km using the nearest neighbour method so that it can be processed with the MODIS-derived PM2.5 and PM10. Each grid of 3 × 3 km for all the criteria parameters (including $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO) was then used for the AQI calculation after their conversion to a point feature. The estimated AQI associated with point feature were then converted to a surface of 3 × 3 km spatial resolution using Kriging interpolation techniques as suggested by Saniei et al. [49].

2.2.4 Calculation of ER%

The ER% is an indicator of health risk and originates due to an increase in air pollution level or increase in the value of AQI. The estimation of ER% is a two-step process, where the first step includes the calculation of relative risk (RR%), and the second step involves the estimation of ER% [5, 31] following Eqs. 7, 8, and 9.

$$RR_i = \exp\left[\beta_i\left(C_i - C_{i,0}\right)\right], \quad C_i > C_{i,0} \quad (7)$$

$$ER_i = RR_i - 1 \quad (8)$$

$$ER_{total} = \sum_{i=1}^{n} ER_i \quad (9)$$

where RR_i is the Relative Risk of pollutant i, $\boldsymbol{\beta_i}$ is the exposure–response coefficient of additional health risk (Such as mortality) caused by per unit of pollutant i, when it exceeds a threshold concentration (0.038, 0.032, 0.13, 3.7, and 0.081 for $PM_{2.5}$, PM_{10}, NO_2, CO, and SO2 respectively). C_i is the concentration of the pollutant i and $C_{i,0}$ is the threshold concentration ((35, 50, 40, 2, and 50 for $PM_{2.5}$, PM_{10}, NO_2, CO, and SO_2 respectively) of pollutant (when threshold concentration of pollutant is less than the pollutant concentration then the relative risk is greater than 0). ER_i is the excess risk for individual pollutants and ER_{total} is the excess risk associated with all the pollutants. The spatial mapping of ER% was done with a similar process as adopted for the AQI in this study.

3 Results and discussion

Satellite-based air quality assessments in terms of pollutant concentrations, AQI, and ER%, were done using satellite measurements in COVID-19 (April 2020) and NON-COVID (April 2019) scenarios over Haryana, situated in the Northern part of India. The selection of period was done, with the assumption, that the COVID-19 driven lockdown would have resulted in the reduction of pollutant level in the study area as reported for other parts of the world [9, 14, 15, 18, 19, 25, 26]. Validation showed a high correlation between satellites measured concentration of air pollutants with that of ground-based pollutants (r^2 = > 0.5, p = 0.00). This indicates the potential of satellite-based products for regular air quality monitoring and ER% assessment. Our findings regarding the reduction in air pollution concentration due to COVID-19 driven lockdown were consistent with Ranja et al. [4], Sharma et al. [5], Siddiqui et al. [6], Sur et al. [12], and Singh and Nanda [27], among others. Objective-wise descriptions of results are described in forthcoming sections.

3.1 Validation of satellite derived pollutants

The validation results are presented in Fig. 3a–f and Table 2 respectively, for AOD, $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO. Validation for CH_4 could not be done due to the lack of ground data related to CH_4. Results showed consistently significant agreement between satellite-derived pollutants and ground-based pollutants.

3.2 Variation in satellite based air pollutants in response to lockdown

Variations in the concentration of air pollutants are presented in Fig. 4a–g. State-level statistics for all the Pollutants for 2019 and 2020 are presented in Table 4 and a decrease/increase in the concentrations (as a result of COVID-19 driven lockdown) is presented in Table 5. Pollutant-wise concentration variations are described in forthcoming sub-sections.

3.2.1 AOD variations

AOD is an indicator of air pollution. Industrial activities, transport, and biomass burning along with the natural dusty air current from the desert are the central sources of AOD over the study area. The AOD showed varying patterns over Haryana (Fig. 4a). The AOD for April month were ranging from 0 to 1.35 for both 2019 to 2020. Relatively high AOD were obtained in the National Capital Region (NCR) districts of Haryana for both years [27]. However,

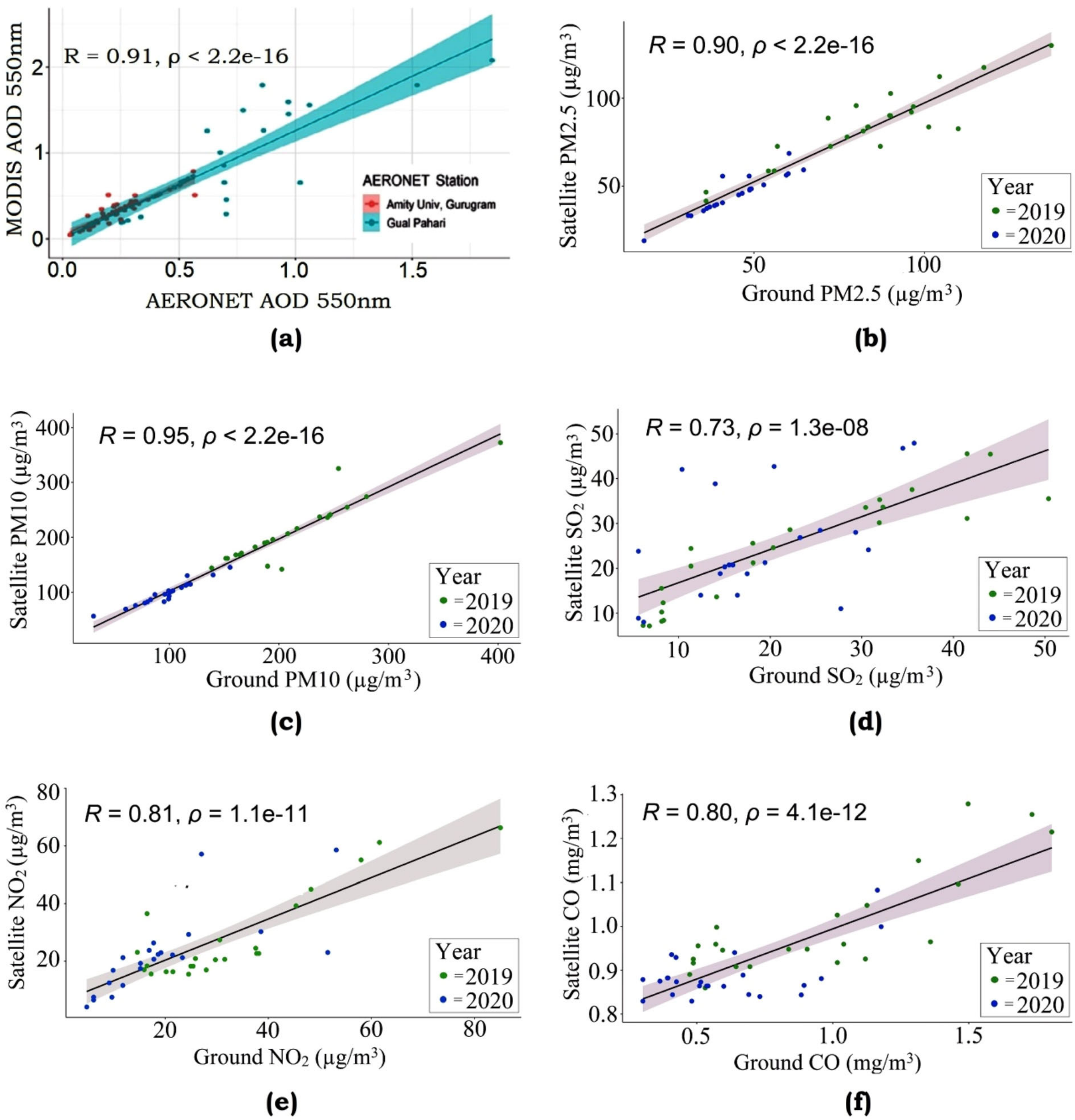


Fig. 3 Scatter plots for the validation of satellite derived parameters with ground measurements during April 2019 and 2020: **a** AOD (2016–2019, Goswami et al., 2020, Red dots presents Amity University, Gurgram and Blue dots presentsGual Pahari, Gurgram Locations), **b** PM2.5, **c** PM10, **d** SO2, **e** NO2, **f** CO

in the year of lockdown, the AOD concentration was very less as compared to the AOD concentration in 2019 (Fig. 4a).

The average AOD in the April month of the year 2019 was 0.626 ± 0.07 with a minimum of 0.073 (in Mahendragarh district) and a maximum of 0.947 (in Kaithal district). The average AOD in the same month of the year 2020 during lockdown was 0.386 ± 0.058 with a minimum $-$ 0.05 (in Bhiwani district) and a maximum of 0.651 (in Sonipat district). Both the average and standard deviation

Table 2 Validation of satellite derived pollution parameters

Pollutant	R	R^2	*p* value	df	t-value	SE
AOD	0.91	0.83	$2.2e{-}16 \approx 0$	85	20.235	0.03311
PM2.5	0.90	0.82	$2.2e{-}16 \approx 0$	42	20.692	0.04914
PM10	0.95	0.90	$2.2e{-}16 \approx 0$	43	26.399	0.03774
SO2	0.73	0.53	$1.3e{-}08 \approx 0$	43	6.9858	0.10382
NO2	0.81	0.66	$1.1e{-}11 \approx 0$	43	9.1841	0.09434
CO	0.80	0.65	$4.1e{-}12 \approx 0$	45	9.3479	0.104313

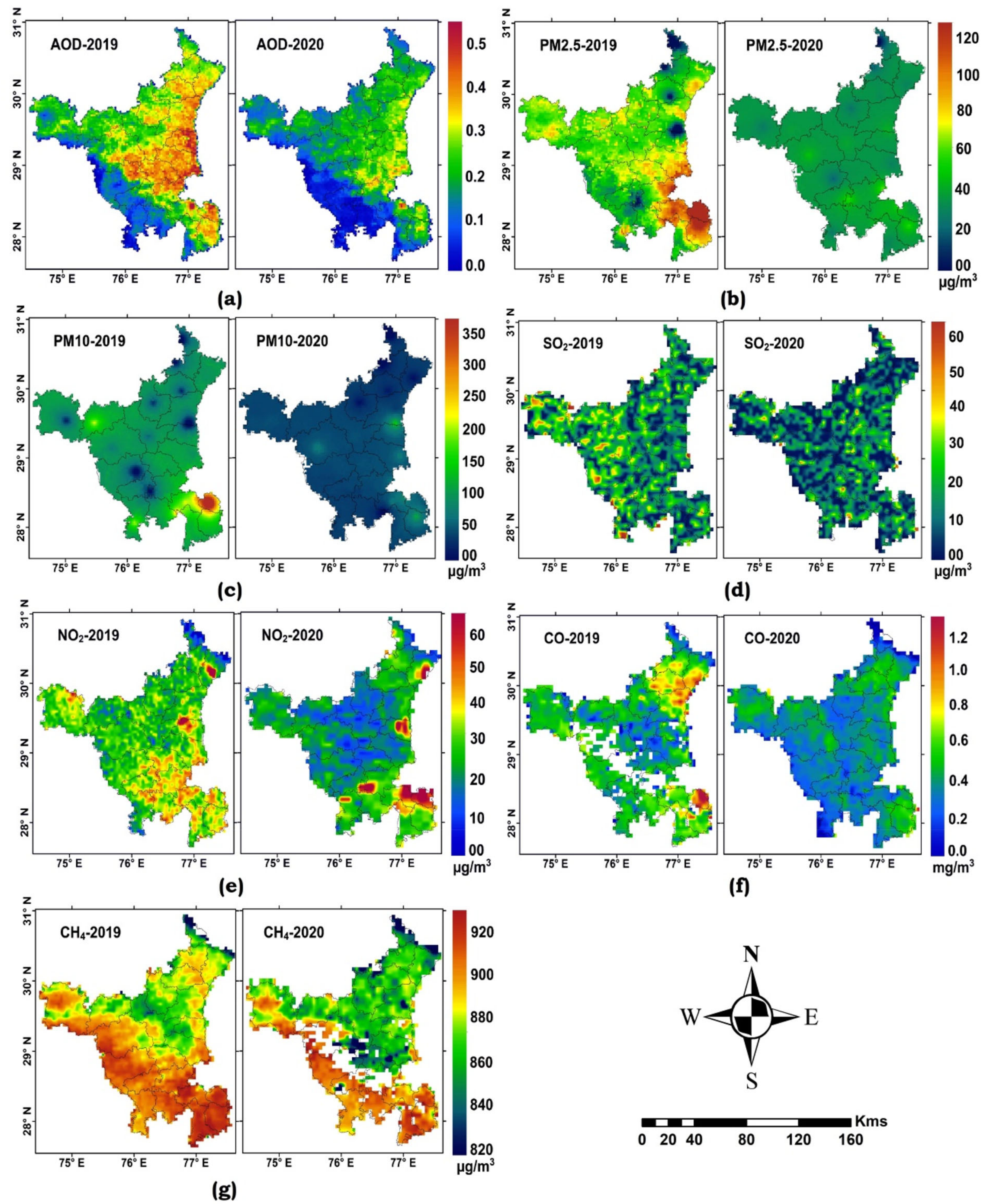


Fig. 4 Spatial varition in average conectartion of pollutants during April 2019 (left), and 2020 (right): **a** AOD, **b** PM2.5, **c** PM10, **d** SO2, **e** NO2, **f** CO, **g** CH4

(SD) were less during the lockdown period, and the average was significantly reduced ($p = 0.05$), showing the reduced level of pollutant gasses in the atmosphere during the lockdown. A total of 38% decrease was observed in average AOD due to COVID-19 lockdown (Table 3).

High AOD concentration over Haryana is attributed to the contribution of agriculture practices, crop residue

Table 3 State of air pollutants over various stations

Pollutants during April 2019/2020 in μg/m^3 except for AOD (which is unit less) and CO (mg/m^3)							
Location name	AOD	PM2.5	PM10	SO2	NO2	CO	CH4
Rohtak	0.57/0.38	82.97/43.11	199.60/100.59	23.7/17.8	22.86/14.47	0.90/0.88	889.34/867.56
Faridabad	0.60/0.37	106.41/46.59	283.26/108.17	23.1/18.1	24.06/35.85	1.08/0.91	905.39/903.22
Yamunanagar	0.45/0.27	80.25/42.23	197.94/94.27	20.4/11.5	19.76/19.03	0.98/0.90	881.77/874.94
Charkhi Dadri	0.41/0.24	74.43/44.91	189.45/98.32	23.5/18.1	23.22/16.96	0.91/0.88	899.61/890.89
Hisar	0.47/0.34	79.31/44.50	198.43/101.59	33.2/13.8	19.25/15.40	0.91/0.89	894.31/887.79
Jind	0.52/0.37	79.89/43.57	197.27/99.94	24.1/20.8	19.15/13.46	0.89/0.88	877.13/874.01
Palwal	0.60/0.39	91.24/47.00	219.19/109.53	21.8/22.3	23.47/21.00	0.95/0.93	907.06/899.30
Kaithal	0.54/0.33	79.95/41.84	193.73/95.48	22.1/14.6	18.83/13.70	0.91/0.88	881.45/875.93
Karnal	0.62/0.32	77.34/43.58	191.45/102.82	18.0/18.3	20.24/16.71	0.97/0.90	883.59/876.90
Gurgaon	0.50/0.31	90.20/47.47	230.71/103.71	21.5/13.4	24.19/27.18	0.96/0.88	903.66/895.32
Bhiwani	0.42/0.25	76.98/42.38	191.09/98.92	28.2/14.5	19.93/15.19	0.92/0.87	900.45/896.68
Mahendergarh	0.28/0.14	75.49/43.15	203.38/97.69	31.3/18.8	19.65/18.56	0.92/0.86	896.43/894.66
Kurukshetra	0.54/0.30	75.83/42.24	192.10/94.40	24.1/16.5	18.90/17.34	1.00/0.92	886.88/876.46
Panchkula	0.33/0.22	64.88/35.31	182.63/88.24	24.1/14.5	12.59/16.03	0.87/0.82	860.87/858.16
Panipat	0.62/0.34	77.38/43.55	192.71/107.32	18.9/21.7	24.36/22.64	0.91/0.89	883.07/881.37
Mewat	0.43/0.25	80.75/43.44	209.79/100.16	17.1/14.3	22.44/21.31	0.96/0.90	907.13/903.90
Fatehbad	0.51/0.33	79.87/43.60	207.85/99.44	27.7/13.4	18.04/15.35	0.90/0.90	885.12/881.34
Sirsa	0.48/0.32	80.3/42.58	196.42/99.41	31.0/15.2	21.28/16.75	0.92/0.90	891.91/889.98
Sonipat	0.63/0.38	85.32/42.67	201.08/103.19	19.2/15.8	21.30/15.60	0.90/0.90	885.80/874.86
Rewari	0.42/0.18	78.28/45.31	204.64/94.92	22.9/16.5	23.63/19.29	0.94/0.88	901.72/899.91
Jhajjar	0.52/0.35	82.18/47.40	198.59/100.55	24.2/18.9	24.73/22.71	0.92/0.87	899.36/892.45
Ambala	0.44/0.27	73.37/40.95	190.61/92.03	22.4/13.5	18.86/18.36	0.96/0.90	884.44/876.87
Average	0.49/0.30	80.57/43.52	203.27/99.58	23.7/16.5	20.94/18.77	0.93/0.89	891.20/885.11

burning, vehicular pollution, and natural dusty wind, among others [4, 27, 28]. The range of previous year AOD and mean concentration of last four years (also reported in another study by Goswami and Singh [56]) were higher than the current year. However, in 2020, the AOD decreased by 38% as compared to the previous year. Similar results have been reported by Ranjan et al. over Indian region [4]. The low AOD values are attributed due to the COVID-19 driven lockdown. Reduced vehicle movement, reduced agriculture practices, and reduced burning of biomass have created the total decrease in AOD [4, 27]. Our findings show consistency with Ranjan et al. [4], Sharma et al. [5], and Singh and Nanda [27].

3.2.2 $PM_{2.5}$ and PM_{10} variation

The $PM_{2.5}$ was ranging from 17.34 to 129.6 μg/m^3. $PM_{2.5}$ concentration was found to be higher during April 2019 as compared to April 2020 (Fig. 4b). The average concentration of the $PM_{2.5}$ for the year 2019 (without lockdown) was 106 ± 4.527 μg/m^3. At the same time, the $PM_{2.5}$ concentration for the year 2020 (during lockdown) was 47.5 ± 1.64 μg/m^3. This showed a total of 55% reduction in the level of $PM_{2.5}$ due to lockdown (Table 4). Faridabad was found to be with high $PM_{2.5}$ concentration.

Satellite-based PM10 showed high agreement with ground-based data, similar to other studies of [1, 29]. The PM_{10} was ranging from 48.29 to 372.45 μg/m^3. The PM_{10} concentration was found to be higher during April 2019 as compared to the concentration of PM_{10} in April 2020 (Fig. 4c). The average concentration of the PM_{10} for the April month of the year 2019 (without lockdown) was 283 ± 8.5 μg/m^3. At the same time, the PM_{10} concentration for the April month of the year 2020 (during lockdown) was 109.5 ± 3.6 μg/m^3. This showed a total of 61% reduction in the level of PM_{10} due to lockdown (Table 4). The PM_{10} concentration was found to be very high over the Faridabad area in the year 2019.

$PM_{2.5}$ and PM_{10} showed a 55% and 61% decrease in concentration due to lockdown. Similar reduction in the $PM_{2.5}$ and PM_{10} were observed in Baghdad [9], Malaysia [19], South America [17], and China [26] among others. The major source of $PM_{2.5}$ and PM_{10} in this region is the natural dusty wind, vehicle emissions, industrial emissions,

Table 4 Statistics of pollutant concentration over Haryana in the month April 2019 and 2020

Parameter#	Year	Min	Max	Mean	STD
AOD**	2019	0.073	0.947	0.626	0.074
	2020	− 0.050	0.651	0.386	0.058
PM2.5**	2019	41.554	129.612	106.413	4.527
	2020	17.345	59.204	47.467	1.647
PM10**	2019	141.773	372.449	283.264	8.524
	2020	48.290	145.250	109.531	3.559
SO2**	2019	0.00	110.55	23.73	7.85
	2020	0.00	80.73	16.52	7.03
NO2*	2019	20.02	61.14	20.94	3.75
	2020	27.49	49.02	18.77	3.93
CO**	2019	0.82	1.04	0.93	0.04
	2020	0.83	0.94	0.89	0.02
CH4*	2019	871.23	904.30	891.20	6.82
	2020	853.79	902.42	885.11	9.77

#All the variable unit is in µg/m^3 except for CO which is measured in mg/m^3

Parameters* = means difference before and during COVID-19 are significant at $p = 0.05$, Parameters** = means of before and during COVID-19 are significant at $p = 0.00$

and stubble burning [10, 27, 28]. The districts that fall in the NCR region (i.e. Faridabad, Gurugram, Jhajjar, and Sonipat) showed high $PM_{2.5}$ values even in the lockdown scenario [27]. This may be due to the limited movement of vehicles in these regions along with agriculture residue burning which is prevalent during this period in normal years.

3.2.3 SO_2 variation

SO_2 were found to be consistently higher and spatially variable in non-COVID scenario i.e. in the April month of the year 2019, as compared to April 2020 (Fig. 4d). The effect of COVID-19 driven lockdown on SO_2 concentration was seen in the form of a reduction of 31%. The average SO_2 in the April month of the year 2019 was 23.7 ± 7.85 (µg/m^3) and for April 2020 it was 16.5 ± 7.03 (µg/m^3).

A significant reduction of 31% ($p = 0.00$) was observed in SO_2 over the region, during COVID-19 scenario. The reduction is attributed to the lockdown as most of the industrial activities, vehicular movements, and Brick cline operations were stopped during COVID-19. Similar reductions (19.51%) in the SO_2 concentration were observed over South and South East Asian region due to lockdown amid COVID-19 [20].

3.2.4 NO_2 variation

NO_2 was also found to be higher in the non-COVID scenario (Fig. 4e). The NO_2 values were ranging from 20.02 (µg/m^3) to 61.14 (µg/m^3) with an average 20.94 ± 3.75 (µg/m^3) for April 2019 which get reduced by 10% to reach an average of 18.77 ± 3.93 (µg/m^3) for April 2020. The difference in mean concentration was significant ($p = 0.05$).

NO_2 also showed a decrease in concentration and results were following other studies from across the world such as Siddiqui et al. and Sur et al. [6, 12] in India, Dantas et al. [13] in Brazil, Brimblecombe and Lai [21] in China, and Jephcote et al. [22] in United Kingdom (UK). Though the decrease in NO_2 concentration was significant ($p = 0.05$), it decreased less as compared to other pollutants (except CO and CH_4). This may be attributed due to the vehicle movements in local areas [22] for the distribution of facilities to the migrants and low-income group peoples.

3.2.5 CO variation

CO mainly originates from the incomplete combustion of fossil fuel. The spatial distribution of CO concentration was found to be decreasing in the year 2020 (Fig. 4f). Spatial statistics at the district level show a 5% decrease (Tables 4 and 5). Gurugram, Faridabad, and districts near Yamunanagar were having very high CO concentration in April 2019 which gets reduced in the COVID-19 scenario.

CO showed a decrease in concentration by 5% in the strict lockdown scenario. CO was found to be high in the Faridabad district during April month of the year 2019 which get significantly reduced in the April month of the year 2020 by 15%. A similar decrease was observed in the northern districts (Karnal, Kurukshetra, Ambala, and Yamunanagar) of the state. The industrial operations were closed during the COVID-19 lockdown and thus decrease in the pollution level was observed similar to the others

Table 5 Decrease in Air pollutants, AQI and ER% due to COVID-19

Year	AOD	PM2.5	PM10	SO2	NO2	CO	CH4	AQI	ER%
2019	0.63	106.41	283.26	23.7	20.94	0.93	891.20	176.02	6.78
2020	0.39	47.47	109.53	16.5	18.77	0.89	885.11	98.86	1.94
Difference	0.24	58.95	173.73	7.2	2.18	0.05	6.09	77.16	4.84
%Decrease	38.36	55.39	61.33	30.69	10.39	5.09	0.1	43.83	71.37

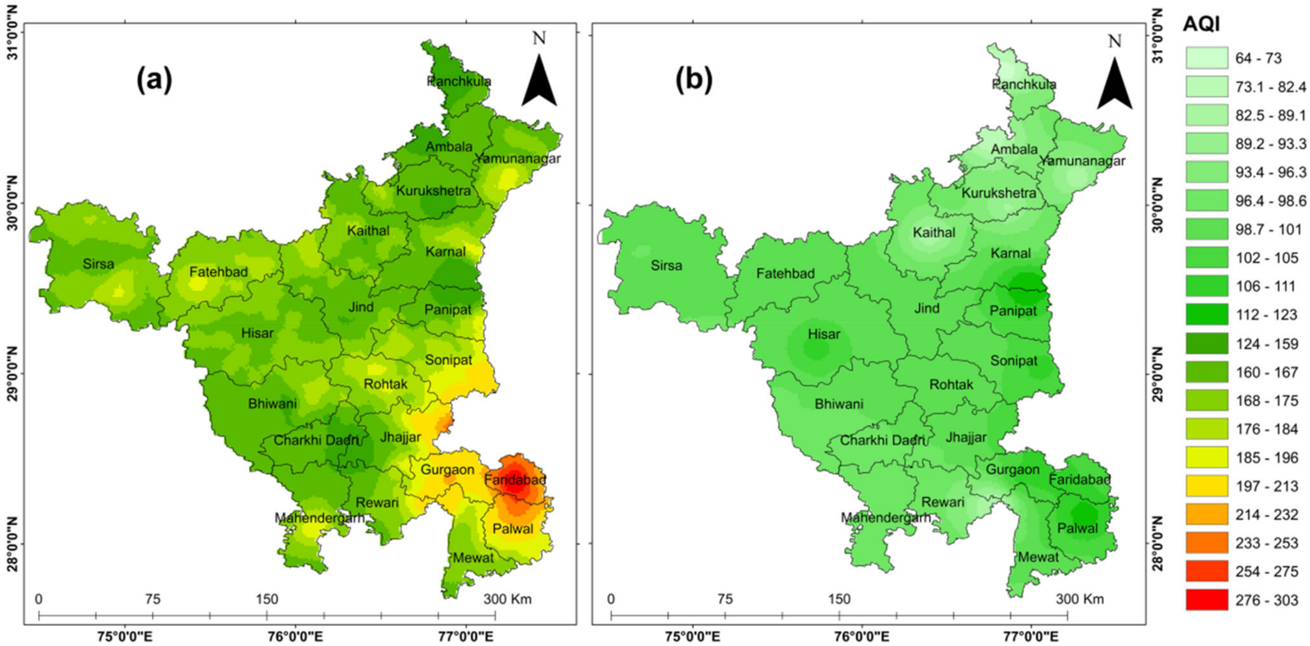


Fig. 5 AQI for the month of April, **a** 2019, and **b** 2020

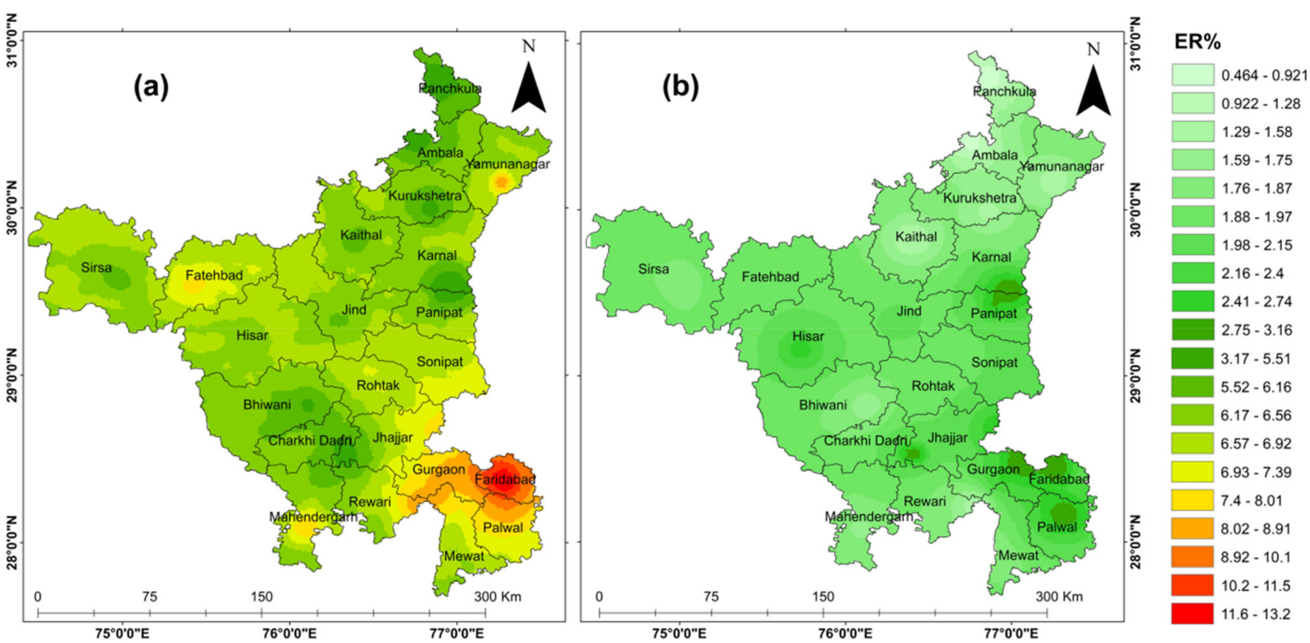


Fig. 6 ER% for the month of April, **a** 2019, and **b** 2020

[21]. The decrease in the CO was actual with high confidence at $p < 0.00$. Further, coal burning in the street restaurant and stubble burning in the open field has also reduced due to COVID-19 driven lockdown, which further reduces the CO concentration over these regions.

3.2.6 CH_4 variation

CH_4 concentration was consistent during the lockdown period at the district level statistics. However, spatial distribution showed higher CH_4 concentration in non-COVID scenario i.e. in the year 2019, especially in Gurugram, Faridabad, and Palwal region. Southern portions were found to be with high CH_4 concentration (Fig. 4g). Only a

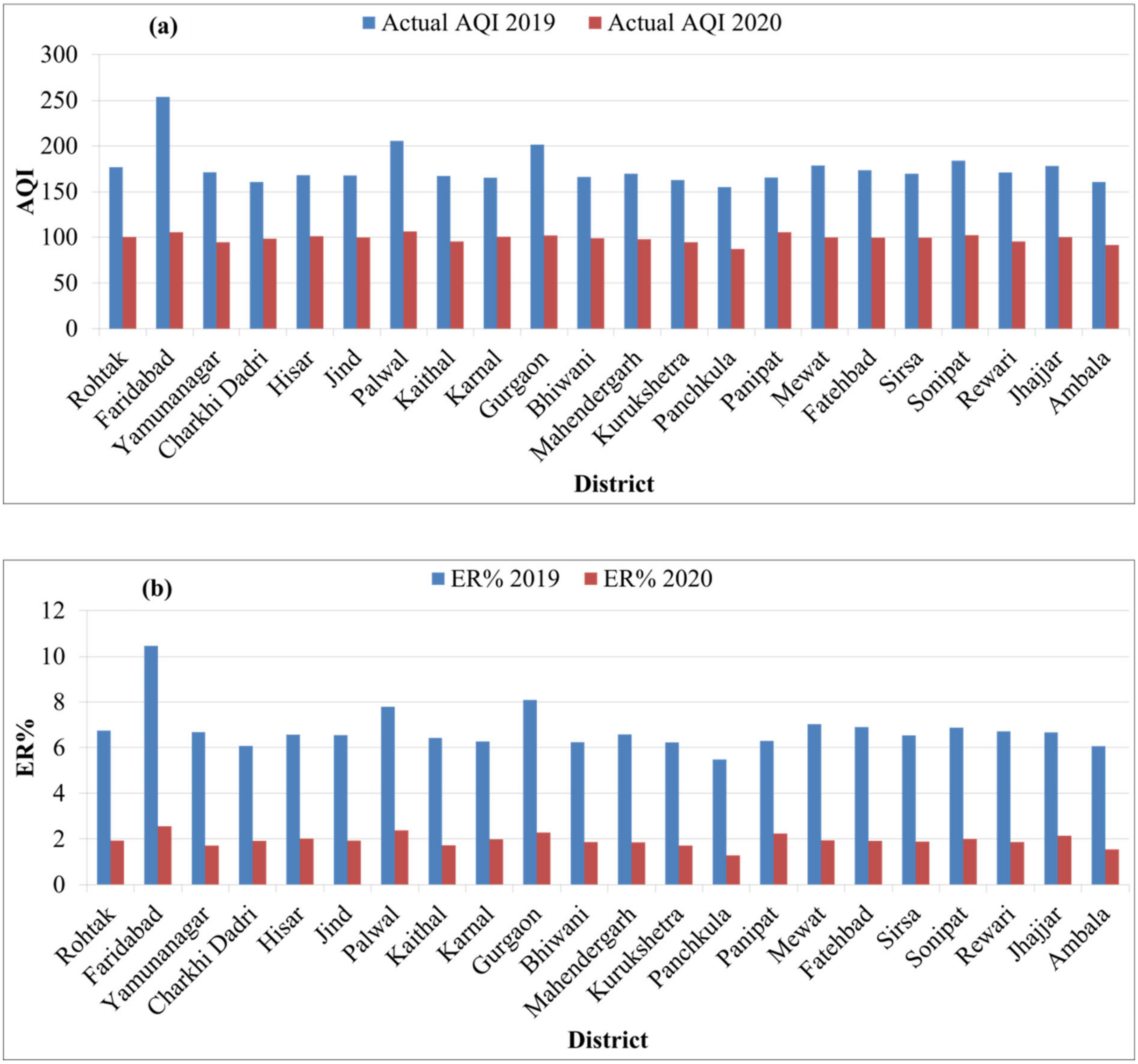


Fig. 7 District-wise, **a** AQI, and **b** ER%, for entire Haryana, before (blue bars) and during (red bars) COVID-19 lockdown

1% decrease was observed in CH_4 due to COVID-driven lockdown.

CH_4 concentration was consistent and a minor reduction (1%) was observed. The southern part of the state had shown high CH_4 in both years. The high concentration of CH_4 over southern-districts may be due to emission from higher livestock populations in the southern part of the Haryana, low-lying wet areas, and prevailing wind direction from North (Paddy belt) to South. Small differences in CH_4 during April lockdown may also be attributed to the missing data in the year 2020.

3.3 Impact of COVID-19 on AQI and ER%

Significant reduction in the AQI and ER% were observed (Figs. 5, 6). Impact of COVID-19 on AQI (Fig. 5a, b) was seen in the form of reduced values and improved air quality in the April month of the year 2020 (Fig. 5b) as compared to April 2019 (Fig. 5a). The average AQI was 176 in the April month of the year 2019 while 99 in April 2020. At the district level, the AQI was moderate to unhealthy (for sensitive groups) (Figs. 5a, b, 7a). However, the AQI was consistently higher (> 150) for all the districts in the non-COVID scenario (year, 2019) and at a low to moderate level, i.e. < 100 during the lockdown phase.

All the districts have shown a considerable decrease in the ER% due to lockdown amid COVID-19 (Figs. 6a, b, 7b). Overall, ER% in the state get significantly reduced (p = 0.00). We have also observed a hotspot over the Faridabad district, which is an industrial area. High ER% was also observed for Fatehabad, Mahendragarh, and

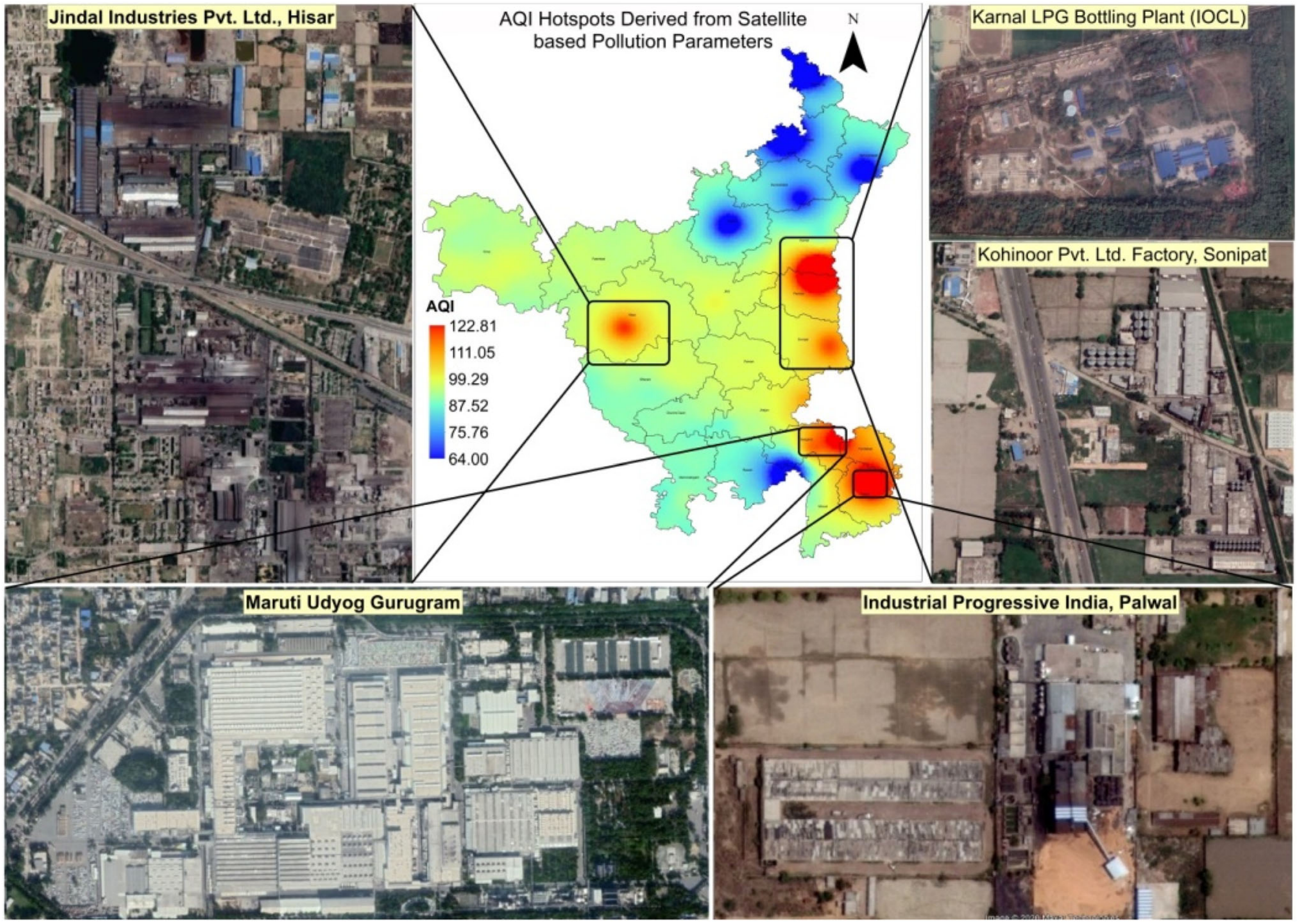


Fig. 8 AQI hotspot visible during lockdown period associated with industries in these areas. The industries showed are only representative and the contribution of other sources/industries is combined

Yamunanagar districts during April 2019. However, the same was not observed for April 2020.

Interestingly, the areas with industries have shown relatively high ER% during the year 2020. This showed that the industrial operations were not stopped during the lockdown period and these areas serve as a hotspot of pollution during lockdown which was otherwise not clear in the year 2019. The AQI, as well as ER%, have shown a gradual decrease i.e. 44% and 71% respectively during the lockdown phase. As we can see in Fig. 6, the hotspot was shown in the parts of Faridabad during April 2019 and 2020.

This part has been further visualised in Google Earth and concluded that this area consists heavily of industry, causing a release of the high volume of particulate matter and other pollutants, due to which there is a hotspot of AQI and ER% (Fig. 8). But still, during the lockdown, these areas have shown a low scale of AQI and decreased considerably from unhealthy to moderate level.

AQI completely based on satellite measured products along with the estimation of ER% is the novelty of the current work. A significant ($p = 0.00$) reduction (44%) in the AQI values was observed due to the reduction in the concentration of criteria pollutants. Our findings were consistent with the [5, 9, 20]. Most of the region comes near to the satisfactory level of AQI as per the Government norms during the lockdown. Improvement in AQI and ER% was observed in all the districts due to reduced industrial operations, agriculture practices like residue burning, and transport activities as a result of COVID-19 driven lockdown enforcement [1, 5, 6, 9, 10, 14, 17].

This analysis showed the industrial pollution was prevailing during the lockdown and highlighted the places of industrial operations even in lockdown enforcement conditions. The method proposed in this work is having global importance and can be applied for the regular monitoring of satellite-based AQI and ER% as both the parameters are in high agreement with ground-based estimates.

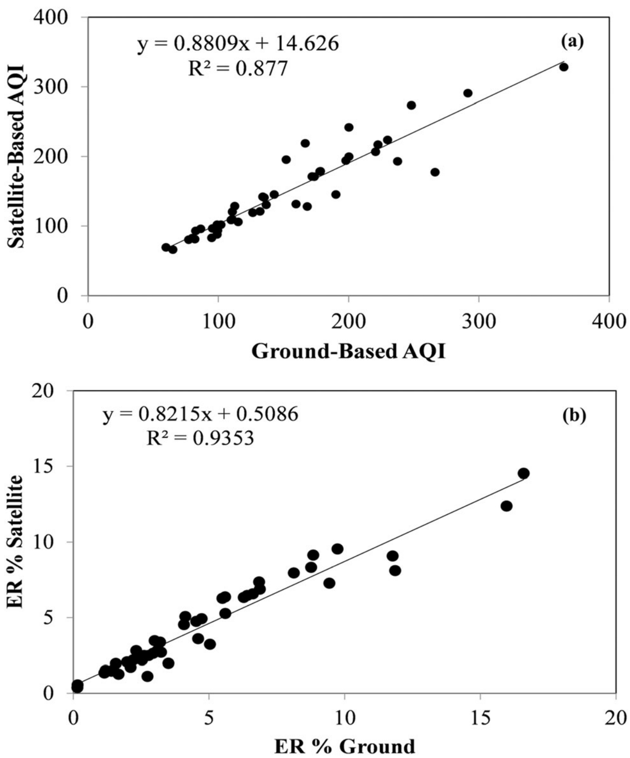


Fig. 9 Scatter plot for satellite and ground-based AQI and ER% validation, **a** AQI and **b** ER%

3.4 Validation of AQI and ER%

We have also validated satellite-based AQI and ER% with ground-based AQI and ER%. A very high correlation was observed between satellite-based AQI and ground-based AQI. The validation results have shown a very good agreement with $r^2 > 0.88$ and 0.94 for AQI and ER%. The Root Mean Square Error (RMSE) for AQI was 23.05 and for ER% it was 1.12. The correlation plots are presented in Fig. 9a, b.

4 Conclusions

Based on the analysis of satellite derived air pollutants, AQI, and ER% for April 2019 (non-COVID) and 2020 (with COVID), over Haryana state, India, some of the key conclusions are drawn. Significant differences in the concentration of almost all the pollutants were observed due to COVID-19 driven lockdown measures. Highest decrease was observed in PM_{10} followed by $PM_{2.5}$, AOD, SO_2, NO_2, CO, and CH_4. Improved air quality (AQI) and Health Risk (ER%) is also resulted from lockdown measures. Satellite data showed a good agreement with ground observations ($r^2 > 0.5$ for all the pollutants). We consider AQI and ER% assessment as an important aspect of our work, where we have used only satellite derived parameters. Satellite-based AQI showed high correlation and less error ($r^2 = 0.88$, and low RMSE of 23.05) with AQI estimated from ground-based data. Significant reduction (44%) in AQI values indicates the improvement of air quality of the study area due to the COVID-19 driven lockdown, which is far better than the decided limit (20–30%) of NCAP target. Simultaneously, the ER% derived from satellite-based data also showed decrease of 71% with respected to the previous year's ER%. The currently identified ER% from satellite-measured parameters showed a very good agreement with ER% calculated from ground-based data with r^2 0.93 and RMSE 1.12. Satellite-based ER% assessed in this study is a novel work and maybe up-scaled to the global scale. It may be beneficial for the health management of the global population.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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